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# Gone with the wind: International migration

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ABSTRACT

This paper adds to the literature on the determinants of international migration. First, we offer a joint analysis of the driving forces of migration capturing year-to-year variations and long-run effects. Second, we analyze the dynamic response of migration to shocks to its determinants.

We start by presenting a theoretical model that allows us to model migration as an augmented gravity equation. We then construct a rich panel data set with 16 destination and 198 origin countries between 1980 and 2015. We find that climate variables are important drivers of migration flows in our sample.

We then estimate a panel vectorautoregressive model showing that the dynamic response of migration is very different across shocks to different driving forces. These findings add to the discussion about the effects of climate shocks on mobility and the concept of trapped population. Our findings carry implications for national and international immigration policies.

## 1. Introduction

"Where shall I go? What shall I do?"

Scarlett O'Hara (Gone with the Wind)

The recent refugee crisis in Europe overshadows an ongoing global trend: international migration.[1] The UN International Migration Report 2015 finds that 3.3% of the world's population, or about 250 million people, are migrants. Besides this increase in the level, the report also shows that the change in migration is accelerating. The effects of migration on destination and origin countries are substantial but complex. We can expect that the scope and impact of migration will increase in the future. In 2010 the World Migration Report projected 405 million international migrants by 2050. This appears to be a rather conservative estimate given increasing global mobility, emerging conflicts, and the predicted 200 million climate migrants by 2050 (cf. Stern Review).

The driving forces of migration are increasingly complex and change over time. We classifiy them into three, broad categories: (socio-)economic, political, and climate-related. Economic factors include better employment and economic opportunities in destination countries (e.g. Mayda, 2010; Ortega and Peri, 2009, 2013). Political variables include freedom and warfare (e.g. Hatton and Williamson, 2003; Moore and Shellman, 2004; Adserà et al., 2016). Most recently, the effect of climate variables on migration have received more attention from policy makers and academics (e.g. Beine and Parsons, 2015; Cattaneo and Peri, 2016). The 2017 World Economic Forum, for example, has declared extreme weather as the most likely risk and second-most impactful one, only trailing weapons of mass destruction.[2]

There is a direct link between climate change and (i) increases in temperature and (ii) a higher incidence, likelihood, and frequency of weather-related disasters (see IPCC, 2012a; Peduzzi, 2005; Herring et al., 2016). Those changes to natural systems already have and are likely to have even more severe effects on countries. Higher temperatures reduce agricultural productivity (cf. Burke et al., 2015b), adversely affect crop yields (cf. Lesk et al., 2016) and, hence, increase agricultural income risk. Along this line, climate change will likely lead to water scarcity and threatens food production (cf. Wheeler and von Braun, 2013). Moreover, climate change will directly impact on health conditions (see WHO, 2009). Along this line, climate change could lead to increased civil unrest and climate-driven conflicts within affected countries due to increased rivalry over scarce resources. Burke et al. (2015a) provide a review of the climate-conflict literature. They conclude that temperature affects the likelihood of intergroup and interpersonal violence. In conclusion, climate change will render some areas

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[1] In this paper we follow the United Nations Recommendations on Statistics of International Migration and define an international migrant as "[…] any person who changes his or her country of usual residence. […]".

[2] The top five in terms of impact also contain water crisis (3rd), natural disasters (4th), and failures to adapt to climate change (5th). The top five most likely risks also feature involuntary migration (2nd) and natural disasters (3rd).

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untenable and will likely have a positive effect on migration out of affected countries.

This paper adds to the literature on the driving forces of migration into OECD countries. It is important to understand the determinants of migration as they will have different effects on the destination and origin country and to develop appropriate policy tools dealing with the expected increase in migration and the expected change in the relative importance of driving forces.

Our paper makes two contributions. First, we offer a *joint* analysis of the driving forces of migration capturing *year-to-year variations* and *long-run effects*. While the literature has discussed various driving forces of migration there is no study jointly explaining it by (socio-)economic, political, and climate-related variables using a large time dimension. We address this important gap in the literature. To do so, we build a rich panel data set of international, bilateral migration flows (regular, permanent migrants) between 16 OECD destination and 198 origin countries over the time span from 1980 to 2015 and include various potential driving forces.

Second, having identified the main drivers of migration, we further exploit the large time-dimension of our data set. Our research question is how migration *dynamically* responds to shocks to its key determinants. In order to address this question, we estimate a panel vector-autoregressive model (PVAR, for short). To the best of our knowledge, this is the first paper looking at the dynamic response of migration to shocks to its driving forces. Therefore, we drive the literature on the determinants of migration into a new direction, emphasizing the importance of the adjustment path of migration.

In contrast to papers using decennial averages for migration flows (cf. Beine and Parsons, 2015; Cattaneo and Peri, 2016), we use annual flows. While this reduces the number of country pairs, it allows us to more precisely link variations in climate variables with migration flows over time. It is, moreover, essential for our analysis of the dynamic response of migration to shocks, were the econometric method requires a large time dimension.

Our main findings are as follows. Our findings show that climate variables generates sizable, negative effects at origin countries. Our results show that higher temperatures increase migration flows and that people avoid warmer destination countries. We find that the number of weather-related disasters at origin increases migration flows to our set of OECD destination countries. Compared to the related literature we find much larger effects of temperature (up to three times) and disasters (about twice as large). This finding supports that a large time dimension is crucial in identifying the effects of climate variables on migration as most of the literature uses decennial averages finding substantially different results.

We then proceed and extend the literature on the non-linear effects of climate variables (cf. Bardsley and Hugo, 2010; Kniveton et al., 2012; McLeman, 2018). We find that countries that rely more heavily on agriculture experience more outward migration while richer origin countries experience less migration from temperature increases. In line with the findings of Howe et al. (2012), we find a significant interaction between temperature and the number of weather-related disasters. Supporting that inference about the long-run consequences of climate change is likely to be done by observing changes in local weather patterns. Finally, in line with the findings of Halliday (2006) we show that a decomposition of weather- and non-weather-related disasters into subcategories reveals different responses of migration to different types of disasters. This is important for policy makers as it implies that the policy response should vary with the type of disaster.

Finally, our panel VAR results show that the dynamic response of migration flows in our sample to shocks to its driving forces is very different across our three categories. We identify shocks using three instruments: volcanic activity for temperature, deaths due to epidemics for political freedom, and non-weather related disasters for income. The response of migration varies in the on-impact response, persistence, and overall adjustment path across different shocks. The response to temperature shocks is particularly interesting. Migration flows in our sample decrease for roughly 5 years before they increase for more then 20 years. This response can be potentially explained by binding liquidity constraints in the short-run and the difficulty to detect and internalize the effects of temperature shocks. Our findings support the "trapped population" concept. Papers such as Gray and Mueller (2012), Black et al. (2013), and Noy (2017) argue that climate shocks can reduce mobility while papers such as Munshi (2003) and Dillon et al. (2011) find an increase in mobility. Our panel VAR allows to add a new perspective to this issue: exploiting the dynamic dimension we find that climate shocks can reduce mobility and decrease migration in our sample.

## 2. Literature review

The literature studying the driving forces of migration can broadly be divided into papers dealing with individual countries (see Karemera et al., 2000, Munshi, 2003, or Clark et al., 2007) and papers using bilateral panel data sets. Within the latter category we can distinguish between "OECD" studies that focus on the migration flows between a large number of origin countries and a small number of high-income (OECD) destination countries and studies that use a large set of origin and destination countries. OECD-type studies are the most prominent ones in the literature which is due to the limited data availability for bilateral migration flows between most countries of the world. Important examples include Mayda (2010), Ortega and Peri (2009, 2012, 2013), Pedersen et al. (2008), and Ruyssen et al. (2014).

The literature on climate-induced migration can be categorized into two streams: studies using temperature and rainfall data and studies using data on disasters. In the following, we focus on panel data studies of the link between climate change and migration (see Obokata et al., 2014 for a survey of the literature not discussed here).

Reuveny and Moore (2009) find a significant push effect of environmental decline. Alexeev et al. (2011) find that weather-related disasters at origin are a push factor increasing migration outflows. Similarly, weather-related disaster at destination act as a pull factor because migrants are used in the recovery and reconstruction effort. Along this line, Drabo and Mbaye (2014) support the finding that natural disasters are positively correlated with migration rates. In contrast, Naudé (2008) does not find conclusive evidence for the effect of disasters on migration.

Backhaus et al. (2015) use bilateral migration data for 11 years between 142 origin and 19 destination countries and find that average annual temperature and precipitation are positively correlated with migration. Two channels are studied to explain the link between migration and climate change: agriculture (cf. Cai et al., 2016) and conflict (cf. Burke et al., 2015a). Reuveny (2007) and Perch-Nielsen et al. (2008) discuss the linkages between climate change, disasters, and migration as well as adaptation strategies. Cattaneo and Peri (2016) show that higher temperatures increase migration into middle income countries. They also stress that higher temperatures reduce migration out of poor countries due to binding liquidity constraints. Further, Marchiori et al. (2012) show that weather anomalies significantly drive migration in Sub-Saharan countries.

Papers using a combination of disasters and temperature (and rainfall) data include studies by Drabo and Mbaye (2014), Beine and Parsons (2015), and Gröschl and Steinwachs (2016). Drabo and Mbaye (2014) use five time observations between 1975 and 2000 for six destination countries and 67 (developing) origin countries. They show that natural disasters and temperature at origin increase, decrease migration rates respectively. Beine and Parsons (2015) do not find a significant effect of climate change on migration flows. In contrast, Gröschl and Steinwachs (2016) do find significant effects of climate change. They use a bilateral migration panel with four time observations explaining migration rates as a function of a hazard index that is composed of disasters and changes in temperature and rainfall. An increase in hazard

intensity increases migration. Those three papers use a small number of time observations therefore only focusing on the long-run effects of climate change.

The three papers closest to ours are the papers by Backhaus et al. (2015), Beine and Parsons (2015), and Gröschl and Steinwachs (2016). None of those papers consider a measure of political freedom different to warfare. However, we argue that political freedom is better captured by a measure of democracy than by a measure of warfare. Further, only Backhaus et al. (2015) use annual data while the other two studies use data with a small time dimension.

## 3. Modelling migration

### 3.1. Theoretical framework

In this section we want to derive a theoretical framework to explain migration. Using reduced-form models, often augmented gravity models (see, e.g. Karemera et al., 2000, Backhaus et al., 2015 or Cai et al., 2016), lack a theoretical foundation, for example, by a rational choice framework. We follow the work by Beine et al. (2011), Grogger and Hanson (2011), and Beine and Parsons (2015) who build on the income maximization approach by Roy (1951) later employed in the migration literature by Borjas (1987). In this theory, homogeneous agents make an optimal decision across multiple destinations on whether to migrate or to stay. They do so by maximizing utility across the set of destinations and the country of origin and relate the expected benefits from migrating to the expected benefits of staying. This theory allows us to derive an empirical specification that resembles an augmented gravity equation.

For the remainder of the paper, assume that the country of origin is $i$ and the destination country, $j$, is element of a set of destination countries $j \in D$, such that $D_d = D \backslash \{i\}$ is the set of possible destinations. In general, utility is assumed to be log-linear and depends on income ($w$) and country-specific characteristics; such as economic factors and variables related to policy and climate.

Utility, $u$, related to migrating is given by

$$u_{ijt} = \ln(w_{jt}) + A_{jt}(\cdot) - C_{ijt}(\cdot) + \varepsilon_{jt}, \tag{1}$$

where $A_{jt}(\cdot)$ denote country $j$'s specific characteristics at time $t$. Further, $C_{ijt}(\cdot)$ gives the cost of migrating from $i$ to $j$ at time $t$. Finally, $\varepsilon_{jt}$ is an error term.

Similarly, utility of staying in country $i$ is

$$u_{iit} = \ln(w_{it}) + A_{it}(\cdot) + \varepsilon_{it}. \tag{2}$$

Assuming that the error term is i.i.d. and that it follows an extreme-value distribution one can apply the results from McFadden (1984).[3] Then, the probability from migrating from $i$ to $j$ is given by

$$\mathbb{P}(u_{ijt} = \max_k u_{ikt}) = \frac{\exp(u_{ijt})}{\sum_k \exp(u_{ikt})}. \tag{3}$$

Then, the bilateral migration rate between countries $i$ and $j$ is

$$\frac{M_{ijt}}{M_{iit}} = \frac{\exp(u_{ijt})}{\sum_k \exp(u_{ikt})}, \tag{4}$$

where $M_{ijt}$ is the number of migrants from country $i$ to $j$ and denotes the bilateral migration flow. Taking logs and re-writing (4) using (1) and (2) gives an equation for the bilateral migration flow

$$\ln(M_{ijt}) = \ln(M_{iit}) + \ln(w_{jt}) - \ln(w_{it}) + A_{jt}(\cdot) - A_{it}(\cdot) - C_{ijt}(\cdot) + \varepsilon_{ijt}, \tag{5}$$

where $\varepsilon_{ijt}$ is an error term. This equation establishes the pull and push factors of migration: the earnings differential across countries, country-specific characteristics at destination and origin, and the costs of migration. In what follows, we will specify the benefits and costs of migrating.

We consider the country-specific characteristics, $A(\cdot)$, for destination and origin: Utility is derived from living in a society defined by political ($Pol$) and economic ($Eco$) factors as well as living under climatic conditions ($Cli$) while migration costs are modelled as a function of dyadic-specific, time-invariant factors, such as distance, common border, or linguistic proximity, denoted by $c_{ij}$, factors constant over time in the origin, $c_i$ and destination, $c_j$, and factors that are destination-specific but time-varying, $c_{jt}$, such as immigration policies. Hence,

$$A_{nt} = A(Pol_{nt}, Eco_{nt}, Cli_{nt}) \ \forall \ n \in \{i, j\}, \tag{6}$$

$$C_{ijt} = C(c_{ij}, c_i, c_j, c_{jt}) \ \forall \ i, j \in D. \tag{7}$$

Using (5) with (6) and (7) gives

$$\begin{aligned} \ln(M_{ijt}) = {} & \ln(M_{iit}) + \ln(w_{jt}) - \ln(w_{it}) + A(Pol_{jt}, Eco_{jt}, Cli_{jt}) \\ & - A(Pol_{it}, Eco_{it}, Cli_{it}) - C(c_{ij}, c_i, c_j, c_{jt}) + \varepsilon_{ijt}. \end{aligned} \tag{8}$$

This equation explains bilateral migration flows by the wage gap, the gap in country-specific characteristics, and the loss incurred due to migrating. Flows, ceteris paribus, will be larger the wider those gaps and the smaller migration costs are.

Assuming separability in the functions $A(\cdot)$ and $C(\cdot)$, gives

$$\begin{aligned} \ln(M_{ijt}) = {} & \ln(M_{iit}) + \ln(w_{jt}) - \ln(w_{it}) + A(Pol_{jt}) + A(Eco_{jt}) + A(Cli_{jt}) \\ & - A(Pol_{it}) - A(Eco_{it}) - A(Cli_{it}) - C(c_{ij}) - C(c_i) - C(c_j) \\ & - C(c_{jt}) + \varepsilon_{ijt}. \end{aligned} \tag{9}$$

In the next section we will derive an estimable equation based upon (9) and discuss the specific variables considered for country-specific characteristics and migration costs as well as our a priori expectation about the effect of each variable on migration flows.

### 3.2. Empirical specification

In line with the recent literature on the determinants of migration we want to estimate an equation similar to an augmented gravity model. We can re-write (9) as

$$\begin{aligned} \ln(M_{ijt}) = {} & \alpha_{it} + \beta_1 \ln(w_{jt}) - \beta_2 \ln(w_{it}) + \beta_3 A(Pol_{jt}) + \beta_4 A(Eco_{jt}) \\ & + \beta_5 A(Cli_{jt}) \\ & - \beta_6 A(Pol_{it}) - \beta_7 A(Eco_{it}) - \beta_8 A(Cli_{it}) - \beta_9 C(c_{ij}) - \beta_{10} C(c_{jt}) \\ & + \varepsilon_{ijt}, \end{aligned} \tag{10}$$

where origin-by-year fixed effects ($\alpha_{it}$) control for all time-varying terms that are constant across destinations but vary across years and country of origin. This will, for example, capture time-invariant origin-related migration costs, $C(c_i)$, and the share of people who choose to stay, $M_{iit}$. As in Ortega and Peri (2013) the origin-by-year fixed effects control for the unobserved heterogeneity between migrants and non-migrants. Here, a different approach is to follow Gröschl and Steinwachs (2016) building on Baier and Bergstrand (2009) and use multilateral resistance terms by adding a first-order Taylor-series expansion. Our results are robust to using this different estimation strategy.

Further, the estimation of (10) poses two challenges. Because our dependent variable - bilateral migration flows - is written in logarithmic terms, we would lose information by dropping the zero observations from the sample. Those are valuable information as they indicate that no migration between two countries took place. The common solution for this problem is to use the bilateral migration flow plus one (cf.

[3] Alternatively, we could follow Ortega and Peri (2012) assuming a more general specification with correlated errors across origin and destination countries. This would give rise to a nested-logit model which would result in an augmented gravity equation identical to ours.

Alexeev et al., 2011; Ortega and Peri, 2009, 2012, 2013; Cai et al., 2016).[4] Then, we can use OLS to obtain our estimates. However, as shown by Santos Silva and Tenreyro (2006, 2011), if the variance of the error term depends on the covariates of the migration rate, consistency of OLS would be violated. This problem can be circumvented by using the Poisson Pseudo-Maximum Likelihood (PPML, for short) estimator. In this case, the zero observations are explicitly included. Unfortunately, the PPML estimator is not the correct estimator for this kind of data because of overdispersion and excess zeros (see Burger et al., 2009). The appropriate estimator is, for example, a negative binomial regression. We will provide robustness checks to our key results using those estimators. Finally, we use clustered standard errors at the country-pair level (cf. Mayda, 2010; Ortega and Peri, 2013) for all regressions.[5]

Economic variables include demographic factors and macroeconomic factors (share of young population and GDP). A higher share of trade in GDP should be a proxy variable for the (cultural) openness of a country and, therefore, should increase migration. A priori, we would expect that origin countries with a younger population should have higher outward migration flows (cf. Mayda (2010)), due to the greater ease of movement of young people. For destination countries, the effect of a larger share of younger people is unclear. The effect depends on whether migrant labor is a substitute (negative) or a complement (positive) to native labor.

Political variables include wars at origin and between destination and origin and an indicator of the political regime. Wars at origin should increase migration by lowering the utility of staying in the home country through various channels such as increased insecurity and harsher living conditions. Wars between destination and origin could have a positive or a negative effect on migration. On one hand, the destination country might be willing to take on some refugees. On the other hand, a war might reduce incentives to migrate to the opponent. The effect of political freedom is ambiguous as, on the one hand, we expect migration flows to increase in more strongly democratic countries, due to a greater freedom of movement. On the other hand, enjoying more political rights will increase the utility enjoyed in the home country.

Finally, we include two measure of climate change: weather-related disasters and temperature anomalies. As pointed out by Howe et al. (2012), gradual, long-term temperature changes are often difficult to detect and perceptions are likely to be influenced by experiences of changes in local weather patterns; particularly extreme events such as heat waves and floods, i.e. weather-related disasters.

Further, we control for non-weather-related disasters as we expect them to have different effects on migration compared to weather-related disasters. Non-weather-related disasters tend to be rapid-onset with temporary effects, resulting in internal displacement (see Piguet et al., 2011). Halliday (2006), using data for El Salvador, shows that agricultural shocks increased migration towards the United States while migration decreased after an earthquake.

The effect of more weather and non-weather-related disasters in destination countries is, a priori, unclear. It could decrease migration, with people avoiding the negative effects of disasters. Alternatively, the creation of jobs associated with repair and rebuilding could result in an increase in migrant arrivals. We expect that a higher number of weather-related and non-weather-related disasters in the origin country increases incentives to migrate. Weather-related disasters have longer-lasting effects compared to non-weather-related disasters, such as desertification and water-scarcity which threatens food production.

Besides this level effect, we observe an increase in the frequency of weather-related disasters over time. Climate change is likely to shift the distribution of weather-related disasters while it does not affect the distribution of non-weather-related disasters. This implies an increase in the expected effects of weather-related disasters affecting people's decisions to migrate. Further, along the lines of Howe et al. (2012), increases in weather-related disasters should also raise the awareness of the long-run effects of climate change and, therefore, affect the migration decision.

Finally, we expect that higher temperatures at origin increase migration. Increases in temperature are, again, associated with crop failures and declining yields, adversely affecting income and economic growth (see IPCC, 2012a,b, 2014). We therefore expect that this increase in migration should especially hold true for countries that rely heavily on agriculture. However, as stressed by Piguet et al. (2011) and Cattaneo and Peri (2016) liquidity constraints may prevent migration and, therefore, higher temperatures could have a negative effect on migration in poor countries. Further, we expect, ceteris paribus, higher temperatures at destination to reduce migration. The exception would be if the destination country does not heavily depend on agriculture, as migrants may have more opportunities to find work in sectors less affected by climate change.

## 4. Data

### 4.1. Variables

In this paper we build a bilateral panel data set on international migration and a wide range of control variables; merging migration flow data with data on other economic, political, and climatic variables. We use data for 16 destination countries and 198 origin countries over the period 1980–2015.[6] Seven out of our 16 destination countries belong to the twenty countries with the largest number of international migrants in 2015.[7] Further, the sample includes countries with the largest immigrant presence.[8] Period and country choice are dictated by data availability. Overall, this gives us 114,048 observations. Details of key variables are discussed in the next section.

#### 4.1.1. Migration flows

We aim to explain yearly net migration flows (*Mig*) taken from the 2015 Revision of the United Nations' Population Division. We merge this data set with data from the OECD and Ortega and Peri (2013). To be precise, our migration data covers regular, permanent migration. Further, as usual in this literature, the data excludes most illegal immigration, such that we likely underestimate the true migration flows. Our bilateral panel of migration flows includes 83,623 observations, which is roughly 10 times the number used in Mayda (2010), twice the number used in Ortega and Peri (2013), and about 20% more than Beine and Parsons (2015) and Gröschl and Steinwachs (2016).[9] Our data set only contains 16% zero migration flows, which is much lower compared to, for example, Gröschl and Steinwachs (2016) with 65%, or Beine and Parsons (2015) with an average of 55%. This is beneficial as it reduces the bias introduced by transforming the data.

Further, our data set also contains the largest number of time observations compared to the related literature by spanning 36 years. For example, Mayda (2010) covers 16 years, Ortega and Peri (2013) cover

[4] Alternatively, we use the inverse hyperbolic sine transformation (see, e.g., Carroll et al., 2003; Kristjánsdóttir, 2012) which leaves our conclusions unaffected.

[5] For the negative binomial regression we use the observed information matrix to compute standard errors.

[6] A list of all countries can be found in the Supporting Information (table S1).

[7] Those countries, in ranked order, are: the United States, Germany, the United Kingdom, Canada, Australia, Spain, and Italy.

[8] Those countries, in ranked order, are: Australia, Switzerland, New Zealand, Canada, Germany, the United States, and the United Kingdom.

[9] We observe a larger variation in migration flows between country-pairs than within country-pairs. Further, we test for a unit root in migration and GDP but the results are inconclusive. Even if the data would be non-stationary our estimates - assuming a likely cointegration - would still be consistent.

27 years, while others (e.g. Beine and Parsons, 2015; Cattaneo and Peri, 2016; Gröschl and Steinwachs, 2016) use four to five decennial time observations respectively. The second largest number of time observations is used by Adserà et al. (2016) with 30. The advantage of using the decennial data set is that it allows the use of flows between a large number of destination and origin countries. However, those data sets contain a large number of zero flows and the small number of time observations ignores year-to-year variations, especially important for the estimation of the effects of short-term fluctuations, such as disasters and wars. Moreover, using decennial averages will underestimate migration flows because of return migration and onward migration. Therefore, we choose to restrict our data set to 16 destination countries and 198 origin countries, but observing 36 years. This is particularly important for us, because we will estimate a panel VAR to study the dynamic effects of shocks. Hence, in contrast to almost all papers in the literature (with the exception of Adserà et al., 2016 and Cai et al., 2016) we are able to look at the long-run migration tendencies as well as variations in short-run flows.

Within this type of OECD study we offer the largest set of destination/origin pairs (Mayda, 2010: 14/79 and Ortega and Peri, 2013: 15/120) over our sample period. The only exceptions are the studies by Cai et al. (2016) with about 95,000 observations from 163 origin countries into 42 destination countries from 1980 to 2010, the study by Adserà et al. (2016) with roughly 45,000 observations from 30 destination and 223 origin countries over 30 years, and the studies using decennial data.

#### 4.1.2. Migration costs

Migration costs are proxied by the distance between the countries (Distance), a country-pair border dummy (*Border*), a common language dummy (*Language*), and a dummy picking up post-1945 colonial ties (*Colony*). Distance is measured by the geodesic distance taken from the CEPII distance measures. The common border dummy is one if the country-pair shares a common (land) border. The dummy for language is one, if a country-pair has the same official language. The colonial ties dummy is one if the country-pair has been in a colonial relationship after the end of the second World War. All those dummies are time-invariant except the border dummy. Given the German reunification in 1990 and that some countries (Czech Republic, Slovakia, and Slovenia) did not (independently) exist before 1991, 1993 respectively, the border dummy needs to be time-varying.

#### 4.1.3. Economic variables

The data for GDP at destination and origin (*GDP*) is taken from the World Bank and is measured as GDP per capita at constant 2010 U.S. Dollar. Our population measure is the fraction of population aged 15–29 (young population, *Y Population*) taken from the United Nations.

#### 4.1.4. Political variables

We create a (time-varying) dummy for (civil) wars (*War*) in the origin country (e.g. Rwandan Civil War from 1990 to 1994) and for an armed conflict within the country-pair (e.g. Operation Desert Storm in 1991) based upon the history of individual countries. The criterion usually applied is that the conflict killed at least 1000 people per year (cf. Alexeev et al., 2011). In our set of high developed destination countries we do not observe a civil war and, therefore, there is no war dummy for destination countries.

Our measure of the political framework is the polity2 variable from the Polity™ IV project by the Center for Systemic Peace (*Policy*). It is a time-varying indicator varying between 10 (strongly democratic) and −10 (strongly autocratic).

#### 4.1.5. Climate-related variables

Data on temperature (*Temperature*) is taken from the Berkeley Earth database. The time series for temperature gives the temperature anomalies (in °C) relative to the monthly average from 1951 to 1980. A regional temperature field is calculated from a large number of weather monitoring stations which then is averaged into a country-wide measure. We choose data for temperature over data for rainfall for two reasons. First, the Berkeley Earth database allows us to collect data for almost all countries over the 36 years, giving us way more observations compared to the available rainfall data. Second, Dell et al. (2009) show that variations in temperature are the main drivers of the negative effects of weather on the economy.[10]

It might be that changes in temperatures matter most for countries with a high dependence on agriculture. In order to put this hypothesis to the test, we include interactions between temperature and agricultural land (*Agriculture*). Agricultural land includes arable land, permanent cropland, and permanent pastures (for livestock). Arable land is land capable of being ploughed and used to grow crops. We measure agricultural land as percent of total land area. All variables are taken from the World Bank.

Data on the number of disasters ($W - Disaster$ and $NW - Disaster$) is derived from the EM-DAT database from the Centre for Research on the Epidemiology of Disasters (CRED). For an event to be declared as a disaster at least one of the following criteria must be fulfilled: ten or more people killed, hundred or more people affected, a state of emergency is declared, or a call for international assistance is issued. Weather-related disasters are: floods, storms, droughts, and extreme temperature events. Non-weather disasters are: earthquakes, wildfires, landslides, volcanic events, and epidemics.

### 4.2. Descriptive statistics

In the following, we will have a preliminary view on the key variables in our model. Table S2 in the Supporting Information provides summary statistics for all variables.

Fig. 1 shows the total annual migrant inflows into our destination countries. We observe a trend of increasing immigration over the entire sample period, including a sharp peak in the early 1990s that we attribute to the collapse of the Soviet Union, the Iraq war, and several civil wars in Africa (Rwanda, Sudan, and Uganda). The vertical movement we see between 2005 and 2014 could be explained by the effect of the Global Financial crisis and missing data. Then, in 2015 migration flows increase sizably potentially driven by increased migration towards European (e.g. Germany) countries. For example, civil wars in Burundi, Ukraine, South Sudan, Syria, and Yemen, gang violence in El Salvador, Guatemala, and Honduras, as well as record breaking temperatures and increases in disasters likely put upward pressure on migration flows.

We then break migration down into immigration flows by country (see Figs. S1 and S2 in the Supporting Information). We observe a trend of increasing annual immigration in most countries. This trend is particularly strong in Australia, Italy, Spain, the UK, and Germany. Germany is now the second largest host of international migrants, only trailing the United States according to the 2015 United Nations International Migration Report. This increase in migration towards Germany could be explained by the enlargement of the European Union in 2004 and 2007. Italy and Spain also experienced large increases in migration, potentially due to the EU enlargement as well as increased migrant flows from North Africa. Spain experienced a sizable drop in migration numbers across almost all origin countries after 2007 which could be attributed to the Global Financial Crisis. Finally, the peak in immigration observed for the United States in the late 1980s could be a result from the 1986 Immigration Reform and Control Act and is an example for the role of immigration policies.

Besides the canonical variables of interest in the literature, we also

[10] We do check robustness of our results (available upon request) by including data on rainfall which turns out to be insignificant and does not affect the other estimated parameters.

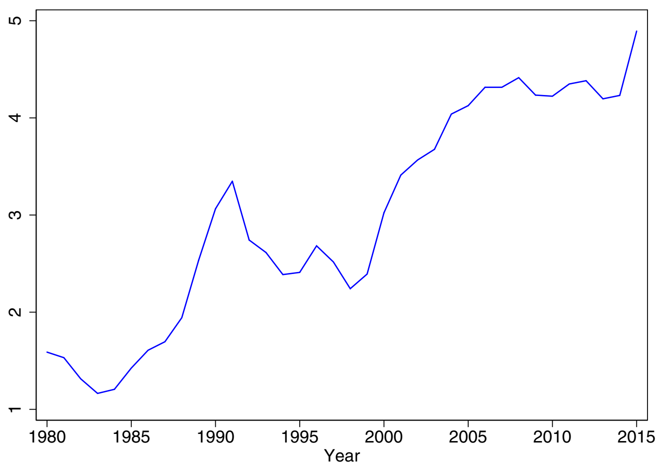


**Fig. 1.** Total migration flows in our sample.

include an indicator for the strength of democracy vs. autocracy as a measure of political freedom. We observe a strong trend of democratization since the late 1980s (see Fig. S5 in the Supporting Information). While at the beginning of our sample the average value of this indicator was −2, indicating that the average country was autocratic, at the end of our sample the average value is 4, indicating an intermediate level of democracy. This increase in democracy can be explained by the so-called "Third Wave" of democracy with democratic processes in Latin America, Asia, Sub-Saharan Africa, and the break-up of the Soviet Union.

Finally, we turn to the discussion of climatic factors. Fig. 2 shows the time series for the total number of weather-related (blue, solid line) and non-weather-related (red, dashed line) disasters across all countries.

The time series for weather-related disasters exhibits a strong upward trend from the beginning of our sample until 2005. From then, we find a slight negative trend such that the number of weather-related disasters stabilizes around 300 per year which is three times as much as in 1980. This observed increase in weather-related disasters can mainly be attributed to increases in the number of floods and, especially towards the end of the sample, extreme temperature events (see Fig. S10 in the Supporting Information). Besides this increase in the number of disasters we also identify a shift in the distribution of disasters (see Fig. S9 in the Supporting Information). While in 1980 it was much more likely that a country did not experience a weather-related disaster, in

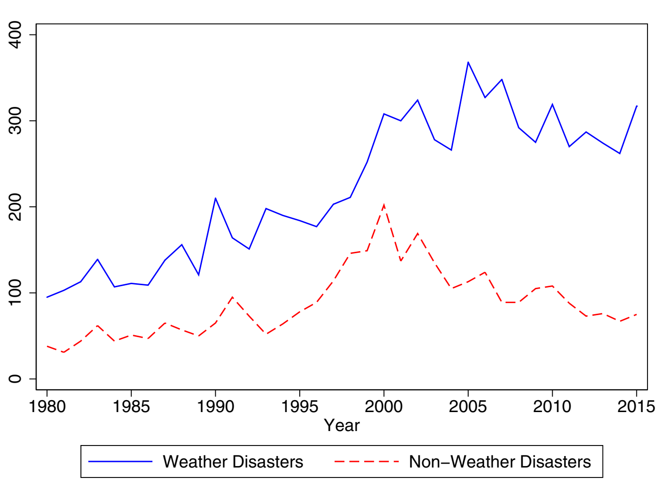


**Fig. 2.** Total number of weather-related and non-weather-related disasters. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

2015 this probability is much smaller and the distribution is right-tailed implying an increase in tail risk.[11] Our observed trend is in line with the prevailing view that climate change increases the number of weather-related disasters, especially floods and heat waves, as well as the frequency of disasters (see IPCC, 2012a, 2014; Peduzzi, 2005).

For the time series of non-weather-related disasters we observe a different pattern. We observe a peak around the end of the millennium which is entirely driven by an increase in the number of epidemics. Apart from this peak the time series as well as its components (cf. Fig. S11 in the Supporting Information) stay stable over time. This should not be surprising as these events are independent of other time-varying factors.

Our measure of long-term climate change is the average temperature anomaly (deviation from trend temperature). Figs. S6–S8 in the Supporting Information show the average temperature anomaly across all countries for each year. We observe a clear upward trend over time. Towards the end of our sample, the average temperature anomaly was close to 0.8°. This finding is in line with the report by the IPCC (2012a,b) documenting an increase of 0.85 °C from 1880 to 2012. As with weather-related disasters, we expect average temperature anomalies to continue to rise as the effects of climate change increase over time.

## 5. Empirical results

### 5.1. Main results

We begin by discussing the results from a basic model of migration. This model is in line with the basic specifications used, for example, by Mayda (2010) and Ortega and Peri (2009, 2012, 2013) and includes the (log) GDP at destination and origin as measures of income, (log) distance, and dummies for common border, language, and colonial ties as measures of migration costs. Table 1 presents our baseline results.

Models 1–7 estimate the basic model using different sets of fixed effects, while models 4 and 5 use alternative estimators. Model 1 only includes year fixed effects and model 2 includes year and destination fixed effects. In the first column the coefficients are not as expected. We find a negative effect of income (GDP) at destination and a positive effect of income at origin. Including destination fixed effects does give the expected positive effect of income at destination. However, income at origin is still positive. This points towards the presence of origin or origin-by-year confounding effects.

Model 3 estimates a model specification including origin fixed effects which is closer to the one implied by our theoretical section. In this specification the signs are as expected and in line with the related literature. To be precise, a 10% increase in GDP at destination will increase migration in our sample by 12.7% (roughly 500,000 migrants per year, in our sample). Ortega and Peri (2013) find a positive effect of around 6% using a different country/time sample. A 10% increase in GDP at origin will reduce migration in our sample by 3.5%. This value is close to the 3.3% reported by Ortega and Peri (2013). The signs of those coefficients are in line with our theoretical model indicating that an increase in GDP at destination acts as a pull factor while a decrease in GDP at origin is a push factor. Further, we proxy migration costs by distance, a common border, language, and colonial ties. We find that a common boarder, in line with Mayda (2010) and Ortega and Peri (2013), does not significantly affect migration flows in our sample. A common language increases migration in our sample by 103.4% which is larger than the 79% reported by Ortega and Peri (2013). Colonial ties increase migration in our sample by 131.64%, which is sizably smaller than the 294% reported by Ortega and Peri (2013). The rational is that

[11] The two years can be accurately compared as 1980 experienced a weak El Niño and 2014–2015 experienced a weak La Niña according to the Oceanic Niño Index.

**Table 1**
Baseline model.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| ln $GDP_j$ | −0.76*** (0.15) | 1.35*** (0.27) | 1.27*** (0.22) | 1.29*** (0.06) | 3.16*** (0.74) | 1.3*** (0.2) | 1.54*** (0.22) |
| ln $GDP_i$ | 0.27*** (0.03) | 0.22*** (0.03) | −0.35*** (0.06) | −0.2*** (0.01) | 0.13 (0.14) | | −0.31*** (0.06) |
| ln $distance_{ij}$ | −0.83*** (0.06) | −1.01*** (0.06) | −0.99*** (0.06) | −0.13*** (0.01) | −0.72*** (0.09) | −0.98*** (0.06) | |
| $Border_{ij}$ | 0.71** (0.35) | 0.69** (0.29) | −0.04 (0.21) | −0.1** (0.05) | 0.4 (0.26) | −0.02 (0.22) | |
| $Language_{ij}$ | 1.3*** (0.18) | 0.19 (0.18) | 0.71*** (0.1) | 0.04 (0.02) | 1.04*** (0.18) | 0.7*** (0.11) | |
| $Colony_{ij}$ | −0.08 (0.23) | 0.24 (0.23) | 0.84*** (0.14) | 0.28*** (0.03) | 1.38*** (0.2) | 0.79*** (0.15) | |
| Obs. | 75,409 | 75,409 | 75,409 | 75,165 | 75,409 | 75,409 | 75,706 |
| ${R_{adj}}^2$ | 0.18 | 0.35 | 0.75 | | 0.52 | 0.76 | 0.88 |
| Estimator | OLS | OLS | OLS | NegBin | PPML | OLS | OLS |
| Fixed effects | | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | No | Yes |
| Destination | No | Yes | Yes | Yes | Yes | Yes | No |
| Origin | No | No | Yes | Yes | Yes | No | No |
| Origin-year | No | No | No | No | No | Yes | No |
| Country-pair | No | No | No | No | No | No | Yes |

Dependent variable: log migration flow. Standard errors are clustered at the country-pair level and shown in parenthesis. Constant not shown. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

colonial ties proxy the cultural difference between destination and origin countries. Countries with similar cultures should have higher migration flows. Further, a 10% increase in distance will reduce migration flows by 9.9% which is exactly the number found by Ortega and Peri (2013). The latter three findings show that migration costs have the expected effects on migration flows. If the costs of migrating are higher, proxied by a larger distance, no colonial ties and a different language, migration, ceteris paribus, will be lower.

This result is confirmed by using the negative binomial regression (model 4). The key differences are that the proxies for migration costs have a much smaller effect on migration. In particular, the effect of distance is sizably reduced. While the negative binomial regression is the appropriate estimator, we also want to show the estimates using the widely used PPML estimator (model 5). Here, we find that the previous estimators underestimate the effect of GDP at destination and that the PPML estimator gives an insignificant effect of GDP at origin. In addition, migration costs now put more emphasis on colonial ties and a common language and less emphasis on distance.

Then, in model 6 we include origin-by-year fixed effects as required by our theoretical Eq. (10). Most important to our analysis is the finding that our results for destination countries from using origin fixed effects hold when using origin-by-year fixed effects. The largest difference is obtained for the effect of colonial ties (0.79 vs. 0.84). In the model controlling for origin-by-year fixed effects this effect is about 6% smaller compared to the model with origin fixed effects. Obviously, in this specification we can not estimate the effect of GDP at origin as any variation at origin is absorbed by the origin-by-year fixed effects. Finally, model 7 uses country-pair fixed effects as another robustness check for the potential bias created by multilateral-resistance. The results show that the coefficients on income at destination and origin are only marginally affected and are, hence, robust. Put differently, the potential bias due to multilateral-resistance appears to be very small.

The next step is to add key variables related to the three categories discussed. Table 2 presents our estimation results.

In the first column (model 3) we again present the results from the baseline model for comparison. Models 8 and 9 add two key policy variables: wars and a measure of political freedom (or democracy). Model 8 adds war at origin and war between destination and origin country. It should be stressed that the dummy for war between destination and origin is mainly driven by the Iraq wars and the war in Afghanistan. Both variables are insignificant and do not affect the migration flows in our sample. This of course does not imply that wars do not generate migration. It shows that these conflicts did not lead to more migration towards the 16 destination countries in our sample. Then, model 9 adds the policy indicator for destination and origin country. We find that policy at origin has a significant positive effect on migration in our sample.[12] An increase in the index by one will increase outward migration by 1%. This finding points towards a push effect of democracy in origin countries. With more democracy and more freedom it is easier for people to move across borders. This is in line with the idea that more autocratic countries restrict the freedom of their citizens. Bertocchi and Strozzi (2008) include a political institutions index and find a positive, significant effect on migration.

Our findings for political variables (war and freedom) are different to the ones obtained in the related literature. Alexeev et al. (2011) and Gröschl and Steinwachs (2016) find that wars at origin, destination have a positive, negative effect on migration flows respectively. Hatton and Williamson (2003) for African countries and Adserà et al. (2016) in a large panel find significant effects of various measures of warfare on migration. Those studies do not control for a separate policy covariate. Given that we find a significant, positive effect of policy at origin, it might be the case that this variable absorbs the effect of wars at origin in our sample. Further, we want to emphasize that our findings do not imply that wars do not generate migration. The results show that wars appear to have no significant effect when we control for political freedom on the migration flows towards the 16 OECD countries in our sample.

Next, we turn to the effect of climate variables: models 10 and 11 add temperature anomalies and weather-related disasters respectively. We find that temperature at destination and origin significantly affect migration flows in our sample. Both effects are in line with our prior expectations. A 10% increase in temperature anomalies at destination (which is an additional increase by 0.08 °C) will reduce migration by roughly 5%. Hence, people avoid destination countries with higher temperatures and the expected, associated adverse effects of climate change. There are, at least, two other explanations for this finding. First, as discussed in the next section, this effect could work through the agricultural dependence of the destination countries. Larger temperature shocks might reduce the labor demand in the agricultural sector and, hence, decreasing this pull factor. Second, our destination

[12] This finding is not driven by the break up of the Soviet Union as it is robust to excluding the former Soviet countries.

**Table 2**
Joint analysis.

| Variable | 3 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|
| ln GDP$_j$ | 1.27$^{***}$ (0.22) | 1.27$^{***}$ (0.22) | 1.19$^{***}$ (0.24) | 1.07$^{***}$ (0.25) | 1.07$^{***}$ (0.25) | 1.59$^{***}$ (0.28) | 1.61$^{***}$ (0.27) | 2.34$^{***}$ (0.28) |
| ln GDP$_i$ | −0.35$^{***}$ (0.06) | −0.35$^{***}$ (0.06) | −0.2$^{***}$ (0.06) | −0.23$^{***}$ (0.06) | −0.24$^{***}$ (0.06) | −0.18$^{***}$ (0.06) | | −0.16$^{***}$ (0.06) |
| ln distance$_{ij}$ | −0.99$^{***}$ (0.06) | −0.99$^{***}$ (0.06) | −0.92$^{***}$ (0.06) | −0.91$^{***}$ (0.06) | −0.91$^{***}$ (0.06) | −0.91$^{***}$ (0.06) | −0.9$^{***}$ (0.07) | |
| Border$_{ij}$ | −0.04 (0.21) | −0.04 (0.21) | −0.03 (0.21) | −0.004 (0.21) | −0.005 (0.21) | −0.001 (0.21) | 0.04 (0.22) | |
| Language$_{ij}$ | 0.71$^{***}$ (0.1) | 0.71$^{***}$ (0.1) | 0.73$^{***}$ (0.11) | 0.71$^{***}$ (0.11) | 0.71$^{***}$ (0.11) | 0.72$^{***}$ (0.11) | 0.7$^{***}$ (0.11) | |
| Colony$_{ij}$ | 0.84$^{***}$ (0.14) | 0.84$^{***}$ (0.14) | 0.99$^{***}$ (0.15) | 1.01$^{***}$ (0.15) | 1.01$^{***}$ (0.15) | 1.01$^{***}$ (0.15) | 0.98$^{***}$ (0.16) | |
| War$_i$ | | 0.05 (0.05) | 0.04 (0.05) | 0.04 (0.05) | 0.04 (0.05) | 0.04 (0.05) | | 0.03 (0.05) |
| War$_{ij}$ | | −0.2 (0.25) | 0.32 (0.24) | 0.3 (0.23) | 0.3 (0.24) | 0.33 (0.23) | 1.7$^{**}$ (0.7) | 0.2 (0.15) |
| Policy$_j$ | | | 0.02 (0.05) | 0.01 (0.05) | 0.01 (0.05) | −0.01 (0.05) | 0.001 (0.05) | 0.02 (0.04) |
| Policy$_i$ | | | 0.01$^{***}$ (0.004) | 0.01$^{***}$ (0.004) | 0.01$^{***}$ (0.004) | 0.01$^{**}$ (0.004) | | 0.005 (0.004) |
| Temperature$_j$ | | | | −0.05$^{***}$ (0.01) | −0.05$^{***}$ (0.01) | −0.05$^{***}$ (0.01) | −0.05$^{***}$ (0.01) | −0.05$^{***}$ (0.01) |
| Temperature$_i$ | | | | 0.03$^{*}$ (0.01) | 0.03$^{**}$ (0.01) | 0.03$^{**}$ (0.01) | | 0.03$^{***}$ (0.01) |
| W-Disaster$_j$ | | | | | 0.0002 (0.003) | −0.003 (0.003) | −0.005$^{**}$ (0.002) | −0.004 (0.002) |
| W-Disaster$_i$ | | | | | 0.02$^{***}$ (0.004) | 0.02$^{***}$ (0.004) | | 0.02$^{***}$ (0.004) |
| Y Population$_j$ | | | | | | −5.21$^{***}$ (1.02) | −5.45$^{***}$ (0.96) | −6.46$^{***}$ (1.01) |
| Y Population$_i$ | | | | | | 3.78$^{***}$ (0.67) | | 3.4$^{***}$ (0.63) |
| Obs. | 75,409 | 75,409 | 64,790 | 61,024 | 61,024 | 61,024 | 61,024 | 61,024 |
| $R_{adj}{}^2$ | 0.75 | 0.75 | 0.75 | 0.74 | 0.74 | 0.75 | 0.75 | 0.89 |
| Estimator | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Fixed effects | | | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Origin | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No |
| Origin-year | No | No | No | No | No | No | Yes | No |
| Country-pair | No | No | No | No | No | No | No | Yes |

Dependent variable: log migration flow. Standard errors are clustered at the country-pair level and shown in parenthesis. Constant not shown. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

countries are rich, "cold" countries. However, even within this group, there are variations in annual average temperatures (and anomalies). For example, the US is "colder" than Italy and this coefficient could pick up that the US are more attractive than Italy.[13]

A 10% increase in temperature at origin will increase migration by 3% (roughly 150,000 migrants per year, in our sample). This implies a sizably stronger effect of temperature at origin compared to income at origin (around 2%) and political freedom at origin (around 1%). The effect is three times larger than the effect found by Cai et al. (2016) and 50% larger than the one found by Backhaus et al. (2015) which supports the importance of a large time dimension and a large set of origin countries. Cattaneo and Peri (2016) find that a 10% increase in temperature at origin increases the emigration rate by around 4%. In contrast, Beine and Parsons (2015) and Gröschl and Steinwachs (2016) do not find significant effects of temperature on migration which, again, could point towards the importance of the time dimension as those studies use five, four decade-time observations respectively.

The effects of climate variables become even more important when we introduce weather-related disasters (model 11). We find that weather-related disasters at origin are significant and increase migration in our sample. In contrast, weather-related disaster at destination do not affect migration in our sample. A 10% increase in the number of disasters at origin (which is equal to 26 disasters for all origin countries combined) will increase migration in our sample by 2%. Alexeev et al. (2011) find an effect of 0.75% for an increase in the number of disasters by 10%, while Beine and Parsons (2015) do not find a significant effect of natural disasters. This effect is slightly smaller than the effect of temperature at origin but still as large as the effect of income at origin. Why do disasters act as push factors? Changes in local weather pattern are used to draw inference about the long-run effects of climate change (cf. Howe et al., 2012) and through this additional channel can affect the migration decision. Moreover, with the shifting distribution of weather-related disasters the expectation effect of more and more frequent disasters has large effects on the migration decision. Finally, weather-related disaster create economic costs that could increase the gap between income at destination and origin country increase the incentive to migrate.

We can draw the conclusion that climate variables have a sizable effect on migration emphasizing the damage done by climate change. Temperature anomalies and weather-related disasters are both significant and quantitatively important. Therefore, our findings imply that climate change already has real, adverse effects in origin countries and acts as an important push factor.

The results presented here are partial effects, i.e. controlling for the effect of, for example, temperature on income, we still find that temperature significantly affects the migration decision. Hence, climate variables, on top of its effect on income and the other covariates, creates push and pull forces. This supports the claim that climate variables are a sizable driver of migration flows. We can, of course, compute the total effect of temperature and weather-related disasters on migration. In regressions not shown here, but available upon request, we find that temperature at origin becomes much more important (0.09) for the migration decision.[14] Therefore, the indirect effect, working through income, is found to be large. When we control for weather-related

[13] This probably is correlated with other factors, but our panel VAR analysis in Section 6 addresses this and shows that the findings are robust.

**Table 3**
Non-linear effects of climate variables.

| Variable | 11 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|
| ln GDP$_j$ | 1.07***<br>(0.25) | 1.05***<br>(0.25) | 1.06***<br>(0.23) | 1.28***<br>(0.25) | 1.07***<br>(0.25) | 1.05***<br>(0.25) |
| ln GDP$_i$ | −0.24***<br>(0.06) | −0.23***<br>(0.06) | | −0.18***<br>(0.06) | −0.25***<br>(0.06) | −0.24***<br>(0.06) |
| Temperature$_j$ | −0.05***<br>(0.01) | −0.05***<br>(0.01) | −0.05***<br>(0.01) | −0.09***<br>(0.01) | −0.05***<br>(0.01) | −0.05***<br>(0.01) |
| Temperature$_i$ | 0.03**<br>(0.01) | 0.03**<br>(0.01) | | 0.02<br>(0.01) | 0.1***<br>(0.02) | 0.03**<br>(0.01) |
| W-disaster$_j$ | 0.0003<br>(0.003) | −0.001<br>(0.002) | −0.003<br>(0.002) | −0.001<br>(0.002) | −0.001<br>(0.002) | −0.001<br>(0.002) |
| W-disaster$_i$ | 0.02***<br>(0.004) | 0.02***<br>(0.004) | | 0.02***<br>(0.004) | 0.02***<br>(0.004) | 0.02***<br>(0.004) |
| NW-disaster$_j$ | | 0.02***<br>(0.006) | 0.02***<br>(0.006) | 0.02***<br>(0.006) | 0.02***<br>(0.006) | 0.02***<br>(0.006) |
| NW-Disaster$_i$ | | 0.02***<br>(0.006) | | 0.02***<br>(0.006) | 0.01**<br>(0.006) | 0.02***<br>(0.006) |
| Agriculture$_j$ | | | | −0.02***<br>(0.005) | | |
| Agriculture$_i$ | | | | 0.005<br>(0.004) | | |
| Temp$_j$ × Agr$_j$ | | | | −0.003***<br>(0.0004) | | |
| Temp$_i$ × Agr$_i$ | | | | 0.004***<br>(0.001) | | |
| GDP$_i$ × Temp$_i$ | | | | | −0.1***<br>(0.01) | |
| W-Dis$_i$ × Temp$_i$ | | | | | | 0.01**<br>(0.005) |
| Obs. | 61,024 | 61,024 | 61,024 | 59,696 | 61,024 | 61,024 |
| $R_{adj}^2$ | 0.74 | 0.74 | 0.75 | 0.75 | 0.75 | 0.74 |
| Estimator | OLS | OLS | OLS | OLS | OLS | OLS |
| Fixed effects | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin-year | No | No | Yes | No | No | No |

Dependent variable: log migration flow. Standard errors are clustered at the country-pair level and shown in parenthesis. Constant as well as distance, border, language, colony, war, and policy results not shown. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

disasters, the effect of temperature at origin becomes smaller (0.03) as weather-related disasters at origin also drive migration (0.02).

What are the potential channels through which climate variables affect migration? As our direct vs. indirect effect discussion has shown, a large part of the effect from temperature works through income. Further, in the next section, we will discuss the potential channel working through agriculture, the so-called agricultural pathway (cf. Marchiori et al., 2012; Cai et al., 2016). Additional channels include health, labor productivity (cf. Heal and Park, 2016), and conflict (cf. Burke et al., 2015a). If climate variables interact with health outcomes, for example through increasing vector-borne diseases, then this could create a stronger incentive to migrate. Similarly, Heal and Park (2016) have shown that temperatures above the thermal comfort zone, i.e. room temperature: between 18 and 22 °C, reduce labor productivity. This could generate an additional effect on the migration decision. Finally, Burke et al. (2015a) review the climate-conflict literature and conclude that temperature, and to a smaller degree rainfall, increase the likelihood of intergroup and interpersonal violence. Mechanisms possibly include psychological channels and changes in the supply of natural resources that may lead to contoversy over allocations.

The last variable to be added is the share of young population (model 12). Young population affects labor market outcomes of migrants by measuring competition. Further, younger migrants should have larger benefits in net present value terms given that they have a longer, expected lifetime. We find that a higher share at destination reduces migration flows in our sample. This could be interpreted such that migrants avoid higher competition in the labor market. Similarly, a higher share of young population will increase migration because, according to our theory, migration costs are - in net present value terms - lower for young people and, hence, migration benefits are larger. It is worth stressing that the effect of GDP at destination increases when we control for the share of young population. While the baseline model implies a value of about 10%, it is now 15.9%. Similarly, the effect of GDP at origin becomes smaller (3.7%–1.8%).

Then, model 13 provides a robustness checks using origin-by-year fixed effects. We find that the signs of all variables are robust. The only exception is the effect of war between destination and origin which is now significant. However, the effect is only significant in this model and we therefore conclude that it is not robust. Further, weather-related disasters at destination are significant, where we also conclude that this result is not robust across specifications. Finally, model 14 uses country-pair fixed effects as an additional robustness check and again shows that the potential bias due to multilateral-resistance is negligible.

At the end of this section we want to stress that we performed several robustness checks (available upon request) of the basic model (3) and model 11 that leave our results unaffected. These checks include: using the migration rates rather than flows, a negative binomial regression for model 12, applying the inverse hyperbolic sine transformation, lagged variables, robust standard errors, different measure for the distance between countries, squared distance and squared temperature, and including other variables such as a common religion dummy, a EU dummy, trade, population density, and life expectancy. We also use the change in the level of the annual average temperature - rather than the temperature anomalies - and find that our results are robust to this different measure of temperature. Finally, we address the effects of the Global Financial Crisis by ending the sample before world output fell. While the size of the coefficients of income at destination and origin become smaller, our results still hold.

### 5.2. Non-linear effects of climate variables

This section focuses on the potential non-linear effects of climate variables. We extend the literature on the non-linear effects of climate variables, for example Bardsley and Hugo (2010), Kniveton et al. (2012), and McLeman (2018). Table 3 presents the estimation results.

The first column presents our baseline model (11) for comparison purposes. Then, model 15 includes non-weather-related disasters. In contrast to the findings of Halliday (2006) we find that non-weather related disasters and weather-related disasters only differ in their quantitative effects. We find that they have a significant positive effect on migration flows in our sample in the destination and origin country. A 10% increase in the number of non-weather-related disasters (which is equal to seven disasters) will lead to a 2% increase in migration flows in our sample. This is in line with our expectation that a larger number of non-weather-related disaster at destination will increase labor demand. This effect will be particularly strong in our sample of high-income destination countries with strong recovery mechanisms (e.g. insurance markets). Our finding is in line with the observations by Alexeev et al. (2011). However, our effect is 30 times stronger than the one reported in their study. Beine and Parsons (2015) do not find a significant effect of natural disasters on migration flows. The positive effect at origin can be explained by the damages generated by those disasters as, for example, earthquakes destroy capital and infrastructure. This acts as a push factor by reducing the benefits of staying at home. Again, this finding is in line with Alexeev et al. (2011) who report a 10 times smaller effect of around 0.2%. In conclusion, non-weather-related disasters do affect migration as a pull factor, mainly labor demand, and as a push factor, by increasing the expected benefits of moving. Model 16 performs a robustness checks using origin-by-year fixed effects as implied by our theoretical equation. We find that our results for destination countries are robust to using origin-by-year fixed

[14] The OLS regressions, similar to Cai et al. (2016), use time and country-pair fixed effects and include: (i) temperature, (ii) temperature and weather-related disasters, and (ii) temperature, weather-related disasters, and income. Results are robust to include rainfall.

effects.

Next, we want to test interaction effects between climate factors and economic variables. Model 17 tests the hypothesis that the effect of temperature is expected to be larger in economies that strongly depend on agriculture. The idea is that the adverse effects of climate change through increasing temperatures will be particularly strong in poor countries where agriculture plays a dominant economic role. In those countries, the effect of water scarcity, lower crop yields, and rivalries over scarce resources should be expected to have stronger effects. In line with this reasoning, we find that for origin countries with a higher share of agriculture, temperature has a stronger positive effect on migration.[15] Similarly, for destination countries with a higher share of agriculture higher temperatures will have a stronger negative effect on migration flows in our sample. The former finding should be intuitive given our a priori expectations. The latter effect shows that people move towards countries experiencing less increases in temperature in line with the reasoning that higher temperatures will have various adverse effects. Our results are in line with the findings by Marchiori et al. (2012) and Cai et al. (2016) showing that the effects of temperature depend on the agricultural share but contrast the finding by Beine and Parsons (2015) who do not find a significant effect.

Then, we test the hypothesis that richer origin countries should be less affected by temperature changes. The results (model 18) show that in richer origin countries higher temperatures have a smaller effect on migration compared to poor origin countries. Intuitively, richer origin countries will have stronger recovery mechanisms to deal with the short- and long-run effects of climate change. In those countries people choose to adapt to the challenges of climate change rather than to migrate.

Finally, model 19 addresses the potential link between weather-related disasters and temperature. This interaction is motivated by the findings of Howe et al. (2012) showing that long-run effects are inferred from changes in local weather patterns. Accordingly, we expect that in countries with more weather-related disasters the awareness of the (future) effects of climate change would be larger and, therefore, temperature changes should have larger effects on migration. We find that this appears to be the case: higher temperatures in countries with more weather-related disasters experience higher migration flows. Alexeev et al. (2011) find the same positive effect at origin.

### 5.3. Decomposing disaster

So far, we assumed that there is only a difference between weather-related and non-weather related disasters. However, it might be the case that there are differences within each category. Therefore, we disaggregate weather- and non-weather-related disasters and analyze the effects of each subcategory on migration. Table 4 presents the estimation results.

The first column in Table 4 presents the baseline model (11). Then, we introduce the subcategories of weather-related disaster (model 20) and the subcategories of non-weather-related disasters (model 21). Our findings are as follows (model 22). Within the weather-related disasters we find a significant positive effect of floods and extreme temperature events at origin in our sample. An increase of 10% in the number of each of these events will individually increase migration by around 3%. This finding supports the viewpoint that increases in the number and frequency of heat waves and floods are the main consequences of climate change (cf. IPCC, 2012a, 2014) and generate real costs (cf. Lesk et al., 2016) that affect the migration decision. Beine and Parsons (2015) using only five (decade) time observations, in contrast, do not find a significant effect of any subcategory of weather-related disasters. Further, Cattaneo and Peri (2016) do not find a significant effect for extreme temperatures using the same data set for migration but different data sets for temperature and disasters.

**Table 4**
Decomposing disaster.

| Variable | 11 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|
| ln GDP$_j$ | 1.07$^{***}$ (0.25) | 1.16$^{***}$ (0.24) | 1.11$^{***}$ (0.23) | 1.1$^{***}$ (0.23) | 1.15$^{***}$ (0.22) |
| ln GDP$_i$ | −0.24$^{***}$ (0.06) | −0.25$^{***}$ (0.05) | −0.25$^{***}$ (0.05) | −0.26$^{***}$ (0.05) | |
| Temperature$_j$ | −0.05$^{***}$ (0.01) | −0.05$^{***}$ (0.01) | −0.04$^{***}$ (0.01) | −0.04$^{***}$ (0.01) | −0.04$^{***}$ (0.01) |
| Temperature$_i$ | 0.03$^{**}$ (0.01) | 0.02 (0.01) | 0.01 (0.01) | 0.02 (0.01) | |
| Flood$_j$ | | 0.02$^{***}$ (0.004) | | 0.02$^{***}$ (0.004) | 0.02$^{***}$ (0.003) |
| Flood$_i$ | | 0.04$^{***}$ (0.01) | | 0.04$^{***}$ (0.005) | |
| Storm$_j$ | | −0.01$^{***}$ (0.003) | | −0.01$^{***}$ (0.002) | −0.01$^{***}$ (0.002) |
| Storm$_i$ | | 0.009 (0.006) | | 0.008 (0.005) | |
| Drought$_j$ | | −0.07$^{***}$ (0.02) | | −0.11$^{***}$ (0.02) | −0.12$^{***}$ (0.01) |
| Drought$_i$ | | 0.01 (0.02) | | 0.01 (0.02) | |
| Ext. Temp$_j$ | | 0.05$^{**}$ (0.01) | | 0.04 (0.01) | 0.04$^{***}$ (0.01) |
| Ext. Temp$_i$ | | 0.05$^{***}$ (0.01) | | 0.05$^{***}$ (0.01) | |
| Quake$_j$ | | | 0.07$^{***}$ (0.01) | 0.08$^{***}$ (0.01) | 0.07$^{***}$ (0.01) |
| Quake$_i$ | | | 0.04$^{***}$ (0.01) | 0.04$^{***}$ (0.01) | |
| Wildfire$_j$ | | | 0.02$^{*}$ (0.01) | 0.03$^{***}$ (0.01) | 0.03$^{***}$ (0.01) |
| Wildfire$_i$ | | | −0.01 (0.01) | −0.03$^{*}$ (0.01) | |
| Landslide$_j$ | | | −0.12$^{***}$ (0.02) | −0.13$^{***}$ (0.02) | −0.14$^{***}$ (0.02) |
| Landslide$_i$ | | | 0.05$^{***}$ (0.01) | 0.04$^{***}$ (0.01) | |
| Volcano$_j$ | | | 0.33$^{***}$ (0.05) | 0.3$^{***}$ (0.05) | 0.29$^{***}$ (0.05) |
| Volcano$_i$ | | | −0.01 (0.02) | −0.01 (0.02) | |
| Epidemic$_j$ | | | −0.06$^{***}$ (0.02) | −0.06$^{***}$ (0.02) | −0.06$^{***}$ (0.02) |
| Epidemic$_i$ | | | 0.02 (0.01) | 0.01 (0.01) | |
| Obs. | 61,024 | 70,708 | 70,708 | 70,708 | 70,708 |
| $R_{adj}^2$ | 0.74 | 0.75 | 0.75 | 0.75 | 0.76 |

Dependent variable: log migration flow. Standard errors are clustered at the country-pair level and shown in parenthesis. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Models 20–22 use year, destination, and origin fixed effects and model 23 uses origin-by-year fixed effects. Constant as well as distance, border, language, colony, war, and policy results not shown.

For non-weather-related disaster at origin, we find that quakes and landslides have a significant, positive effect on migration in our sample, while wildfires decrease migration. Ten percent more quakes, landslides will increase migration by four, 3% respectively. Both findings are in contrast to the previous literature. Beine and Parsons (2015) and Gröschl and Steinwachs (2016) do not find a significant effect for quakes at origin but do not consider landslides. Our results show that quakes and landslides both act as push factors. The damages in capital and infrastructure appear to outweigh the opportunities in the recovery process. According to our theoretical section, we can understand this finding by the negative effects of those disasters on the benefits from country-specific characteristics. Finally, droughts and storms are insignificant in our sample; in line with the findings by Beine and Parsons (2015) and Gröschl and Steinwachs (2016). This should, at least to some degree, be expected given that the number of droughts and storms stays stable over time while we observe an increase in floods and extreme temperature events.

Next, we turn to the effects at destination countries. For weather-related disasters we find a significant positive effect of floods and a negative effect of storms and droughts. Only extreme temperature events have no significant effect. The negative effect of storms and droughts should be intuitive as people want to migrate away from the

[15] The insignificant effect of temperature at origin just shows that at a zero agricultural share, temperature has no effect.

negative effects of climate change. The positive, robust effect of floods is more surprising. It should be related to the positive effect of recovery programs, especially strong in our set of high-income destination countries.

For non-weather-related disasters at destination, quakes, wildfires, and volcanic activities have a positive effect on migration in our sample, while epidemics and landslides reduce migration. However, controlling for origin-by-year fixed effects shows that only the effect and sign of quakes and landslides is robust. The positive effect of quakes, again, can be attributed to increased labor demand in the recovery process. The negative effect of landslides is likely to be driven by the desire of migrants to avoid the negative effects of those disasters.

Overall, we find that it is important to consider not just the total number of weather- and non-weather-related disasters but the subcategories of disasters. In line with the literature on climate change we find that floods and extreme temperatures at origin countries act as push factors. Quakes at destination act as a pull factor while landslides reduce migration.

## 6. Dynamic effects on migration

Previously, we identified the main driving forces of international migration in our sample. This section further exploits the large time-dimension of our data set. We aim at answering the important question how shocks to the key driving forces affect migration flows over time: Does migration increase on impact? For how long does migration increase? Those questions are important for policy makers to develop appropriate tools to deal with the response of migration to shocks.

Given that our data set spans the equivalent of two generations, we are able to estimate a Panel vectorautoregressive model. To the best of our knowledge, this is the first time a PVAR model has been estimated in a large panel data model of migration. Put differently, this is the first paper looking at the dynamic effects of shocks to the driving forces of migration. The only related paper is Boubtane et al. (2013) who use data from 1987 to 2009 for net migration rates in 22 destination countries to estimate a panel VAR with three variables: migration, output, and different measures of (un)employment. They find a positive response of the migration rate to increased income at destination after 2 years lasting for 2 years and an on-impact negative response of higher unemployment lasting for about 2 years. The key differences between our approach and theirs is that we employ a bilateral panel data set, use a large number of variables, and identify our shocks using instrumental variables rather than a Cholesky decomposition.

Technically, we estimate the panel VARX (PVARX (2)) model

$$Y_{i,t} = A_{0,i} + A_{1,i}Y_{i,t-1} + A_{2,i}Y_{i,t-2} + F_iX_t + u_{i,t},\ i = 1, \ldots, N,\ t = 1, \ldots T, \tag{11}$$

where $Y_{i,\ t}$ is the vector of observables of dimension $(1 \times K)$ and $A_i$ is a $(K \times K)$ parameter matrix that may depend on the panel unit $i$. Idiosyncratic errors are given by the $(1 \times K)$ vector $u_{i,\ t}$, where $\mathbb{E}(u_{i,t}) = 0$ and $\mathbb{E}(u_{i,t}'u_{i,t}) = \Sigma$. The dependent variables are allowed to linearly depend on exogenous variables, $X_t$, of dimension $(1 \times N)$ via the associated matrix $F_i$. We estimate the PVARX using IV-GMM with four lags as instruments and standard errors clustered at the country-pair level. Fixed effects are removed by applying a Helmert transformation of the data.

The vector of observables is populated by the significant variables from our previous analysis: GDP at destination and origin, temperature and young population at destination and origin, and weather-related disaster and policy at origin. Further, the most important part of our approach is the identification of the shocks. Our identification strategy is as follows. We aim at identifying the following three shocks: shocks to income at destination, policy at origin, and temperature at origin. We will also investigate the effect of a shock to weather-related disasters at origin, but we argue that these disasters are exogenous and do not require an instrument for identification. To identify the three shocks, we use the following instruments: the number of deaths due to non-weather-related disasters at destination, number of deaths due to epidemics at origin, and the incidence of volcanic activity at origin. The PVAR uses country x year variation to identify shocks. We use variation in the cross-section (e.g. some countries will be affected by volcanic activity) over time to estimate the impact of a variation in, for example, temperature at a given origin country on migration from this origin country to all our destination countries. We then present the average effect in an impulse response function.

Our theoretical assumptions can be summarized as follows. Non-weather-related disasters are exogenous and, therefore, should be a valid instrument to identify movements in GDP. Here, we use the number of deaths rather than the number of non-weather-related disasters as we expect the number of deaths to be a better proxy variable for the strength and impact of the non-weather-related disaster.

Then, we use the number of deaths due to epidemics to identify political freedom. The idea is that epidemics are purely exogenous events, rapid onset with temporary effects, that can lead to large social and economic disruptions (GHRF, 2016). In addition, governments are often blamed for not protecting their citizens and, especially in countries with a history of civil wars, this will lead to increased mistrust, civil unrest and, potentially, civil wars (see The Economist, 2014). Gonzalez-Torres and Esposito (2017) use the Ebola outbreak in 2014/15 to study this relationship and find that one new Ebola infection among 100,000 per capita will increase the probability of conflict in the next period by 10%. Further, this type of conflict is subversive, as it is targeted towards institutions and medical authorities. Further, epidemics will not affect temperatures or weather-related disaster nor should they affect income at destination. Then, we identify weather-related disaster by using the agricultural share, where we mainly use the cross-sectional dimension to identify the shock. Finally, we use volcanic activity as an instrument for temperature. A volcanic eruption has two effects on (the local) climate. Any eruption releases large amounts of sulfur dioxide ($SO_2$) and carbon dioxide ($CO_2$) into the stratosphere. The former sulfur dioxide converts to sulfuric acid which condenses and forms sulfate aerosols. This leads to an increased reflection of sun radiation and, therefore, generates a cooling effect for several years. The latter is a green house gas which increases temperature. Although the amount of carbon dioxide emitted by volcanoes is small compared to the amount created by anthropogenic forcing, large and frequent volcanic eruptions might increase temperatures. Stordal et al. (2017) find that large-scale volcanic events have the potential to increase global temperature (by up to 7 °C) for a short period of time.

Before we discuss the dynamic response we want to briefly discuss the outcome of our identification strategy. First, our instruments do identify the three shocks. More deaths from non-weather-related disasters, i.e. stronger disasters, reduce GDP at destination, as expected. More deaths due to epidemics reduce political freedom at origin. This finding is in line with the findings by Gonzalez-Torres and Esposito (2017). In line with Stordal et al. (2017), volcanic activity has a positive effect on temperature. While the cooling effect of volcanic activity lasts for several years it eventually disappears while the emission of carbon dioxide leads to an increase in temperature. It might also be the case that this variable proxies the emission of carbon dioxide which is in line with its effect on temperature.

Then, Fig. 3 shows the response of migration to identified, one-standard deviation shocks to income at destination, policy at origin, weather-related disasters at origin, and temperature at origin.

We begin by discussing the response of migration in our sample to an income shock at destination. This shock increases the wage gap and acts as a pull factor for migrants. Therefore, as expected, we observe a positive effect on migration flows towards destination countries. The effect reaches its peak of about 6% after roughly 8 years. Further, we find that the response of migration is very persistent lasting for more than 20 years. This can be explained by the effects of migrant networks.

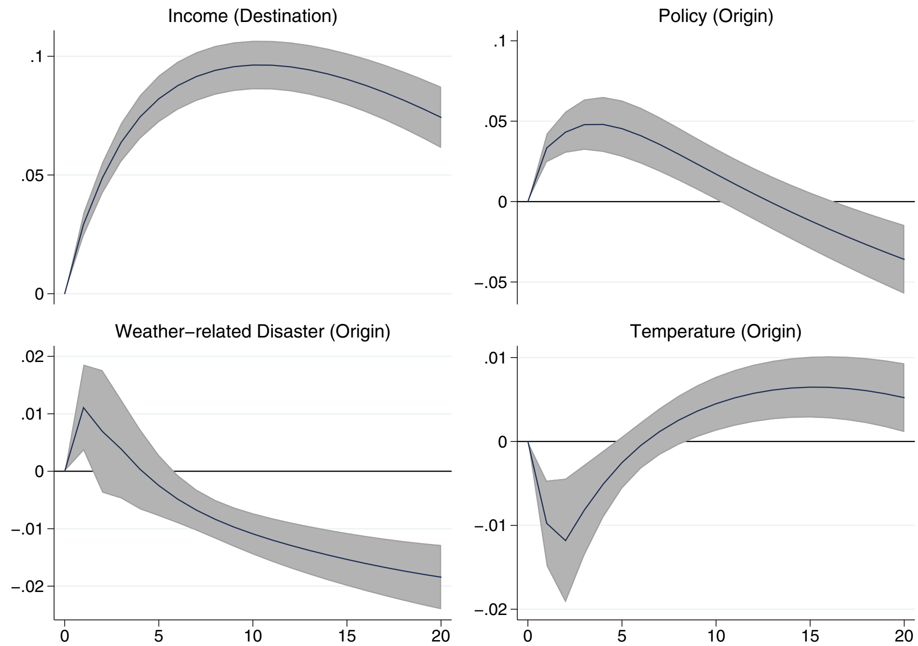


**Fig. 3.** Identified impulse response functions from the PVARX. Figures show mean effect on (log) migration as black line and 90% confidence bands (gray).

Munshi (2003) and Beine et al. (2011, 2015), for example, show that networks reduce the cost of migration and, therefore, act as an endogenous pull factor. This explains the significant coefficient of lagged migration and the high persistence in response to the shock. Further, the income shock itself is expected to have a high autocorrelation, which will increase income at destination and, therefore, the wage gap between destination and origin for a long period of time.

Next, we look at the response of migration in our sample to an increase in political freedom. As already shown in our panel estimates, we find a positive effect on migration flows with a high degree of persistence. The peak effect is reached after about 4 years with a 5% increase in migration. There are two reasons for this finding. First, changes in political institutions usually last for several years (cf. election cycles). For example, 10 years after the Bosnian war (1992–1995) half of the refugees were still outside their homes. Afghanistan still experiences large outward migration flows that started with the 2001 U.S. and allied forces invasion. Towards the end of our period the effect turns negative, which could be because the positive effects of higher political freedom might take time to materialize in the origin country. Hence, the cost-benefit analysis of agents might change over time, when these positive effects materialize.

We then focus on the effects of climate variables: weather-related disasters and temperatures. Temperature shocks generate a surprising and unexpected dynamic response. On impact, migration flows decrease by 1% and stay below the initial level for roughly four to 5 years. After 4 years we observe a positive effect on migration flows with a peak effect of half of a percent lasting for more than 20 years. This pattern can be explained by several factors. First, as stressed by Howe et al. (2012) changes in temperature are difficult to detect and it takes time to fully internalize the effects of temperature shocks. Second, as stressed by Halliday (2006), Piguet et al. (2011), and Cattaneo and Peri (2016) there exist binding liquidity constraints that prevent an on impact increase in outward migration. This holds especially true for poor countries. Why then does migration decrease on impact? This could be driven by high migration costs creating social and economic barriers to migrate. Moreover, Dillon et al. (2011) raise two important points. Households affected by adverse shocks deplete their assets to smooth consumption during a transitory shock. Hence, those resources are not available to finance migration costs. Further, they stress the importance of insurance against income risk via spatial diversification by increasing migration. However, with rising temperatures this insurance channel, at least for the within-country spatial disaggregation, will become less and less efficient. Put differently, in response to a temperature shock households reduce the spatial allocation of labor as this no longer mitigates (agricultural) income risk. As a consequence, migration decreases until the liquidity constraints become non-binding and until the household has accumulated enough assets to finance migration costs. A further thought is that with increasing global temperatures, household members need to migrate further to efficiently spatially disaggregate risk which increases migration costs and, therefore, reduces migration until enough resources could be accumulated.

This result also adds to the discussion about a “trapped population”. Papers such as Gray and Mueller (2012), Black et al. (2013), and Noy (2017) provide evidence that climate shocks can reduce mobility while papers such as Munshi (2003) and Dillon et al. (2011) find an increase in mobility. Our panel VAR allows to add a new perspective to this issue: exploiting the dynamic dimension we find that there is a reduction in mobility and this “trap” binds for about 4 years.

Finally, we find that weather-related disasters have a positive effect in the short-run but a negative effect on migration in the long-run. This is another surprising finding, given that our panel regression pointed towards a significant, robust positive effect. Of course, in the panel regression we looked at the contemporaneous effect and the PVAR uses lags but, nevertheless, this is an unexpected finding. The results show that there is a significant effect on-impact, with a 1% increase in migration. Then, migration flows increase for about 5 years, before they turn negative. The effect is similarly persistent compared to temperature shock discussed earlier. The latter result can be potentially explained by the trapped population concept. There is country-level evidence where disasters reduced mobility and, therefore, migration. Again, the papers by Gray and Mueller (2012), Black et al. (2013), and Noy (2017) show that there is a trapped population effect and that climatic shocks - disaster - can reduce migration. However, our results add the time-dimension to this story. It appears that weather-related disasters cause an immediate increase of migration, potentially people that are able to move will leave. Then, over the longer-run, the trapped population effect appears to dominate. One explanation is that disaster relief and the re-building process might take a longer time to develop effects. Intuitively, disaster can reduce access to resources but increase labor demand for the reconstruction process in the aftermath of the

disaster.

Overall, we can conclude that the dynamic response of migration in our sample to shocks to its driving forces is very different across the three categories: (socio-)economic, political, and climatic. Further, we find that the dynamic response of migration is much more complex compared to the findings from panel estimations. In particular, the on impact response might be very different to the effects obtained in standard regressions. This finding, in combination with the high persistence of the response, has very important policy implications.

## 7. Conclusion

In this paper we add to the literature on the driving forces of migration towards OECD countries. We take two important steps in the direction of understanding the dynamic response of migration to shocks to its drivers. Therefore, we drive the literature on the determinants of migration into a new direction, recognizing the importance of the adjustment process of migration.

We first present a stylized utility maximization model that allows us to derive an estimable augmented gravity equation. Then, we build a rich panel data set of international, bilateral migration flows between 16 destination and 198 origin countries over the period 1980–2015 and include various potential driving forces. In a first step, we identify the key driving forces of migration in order to, in a second step, estimate a panel VAR model and discuss the effects of shocks to these driving forces.

Several results stand out. We find robust evidence that migration towards OECD countries in our sample is an adaptation strategy to deal with the effects of climate change. In combination, the effect of climate change through higher temperatures and an increase in the incidence of disasters is an important driver of the migration decision.

We then investigate whether the effects of temperature are non-linear in line with previous work by Bardsley and Hugo (2010) and Kniveton et al. (2012). Countries that rely predominantly on agriculture suffer from more outward migration while richer origin countries suffer less from temperature increases. We also find a significant interaction between temperature and the number of weather-related disaster in our sample. We also show that a decomposition of weather- and non-weather-related disasters into subcategories reveals different responses of migration to different types of disasters.

Finally, our panel VAR results show that the dynamic response of migration to shocks to its driving forces is very different across the three categories of driving forces, varying across the on impact response, persistence, and the general adjustment path. The response to temperature shocks is particularly interesting. Migration flows in our sample decrease for roughly 5 years before they increase for more then 20 years. This response can be potentially explained by binding liquidity constraints in the short-run and the difficulty to detect and internalize the effects of temperature shocks. Our results adds to the discussion about the concept of a “trapped population”. In line with Gray and Mueller (2012), Black et al. (2013), and Noy (2017) we find evidence that climate shocks can reduce mobility.

In conclusion, our results suggest that climate variables are key drivers of migration. Given the overwhelming evidence about the expected adverse effects of climate change in the future, we can expect that it can become an even more important driver of migration flows in the future.

Finally, our conclusions carry important implications for the current - policy and public - debate about migration. They should be a starting point to study the dynamic response of migration to shocks and build a basis to develop effective policy tools to deal with the anticipated consequences of shocks to driving forces of migration.

Starting with the short-run, our findings imply that national governments should develop flexible national immigration policies and aim for an increased international collaboration in order to ensure a swift response to shocks. For the long-run, developing structural adaptation mechanisms to deal with the anticipated long-run effects on migration is highly recommended. This can include, for example, reinforcing existing rescue mechanisms, the improvement of early warning systems for disasters, limiting land changes, investment into infrastructure projects (e.g. dams and shelters), increasing agricultural productivity (e.g. research and education), limiting carbon dioxide emissions, improving credit market efficiency, increasing social safety nets, and improved access to education and health (see IPCC, 2012b for a detailed list of adaptation and mitigation measures). Another important dimension is foreign aid, i.e. development programs, aimed at increasing economic growth and building resilience, especially in low-income countries. Further, an international agreement on migration, along the lines of the reduction in trade barriers and the free movement of capital, would be highly beneficial. Our results also point out that the speed of the policy response is crucial in limiting the effects of shocks in origin countries and, therefore, the effects on migration.

Given our findings and, especially, the predicted impact of climate change and the increasing global mobility, rewriting *Rhett Butler's* famous line from *Gone with the Wind*, our policy conclusion can be summarized as follows: *“Frankly, my dear, we should give a damn.”*

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloplacha.2019.04.008.

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